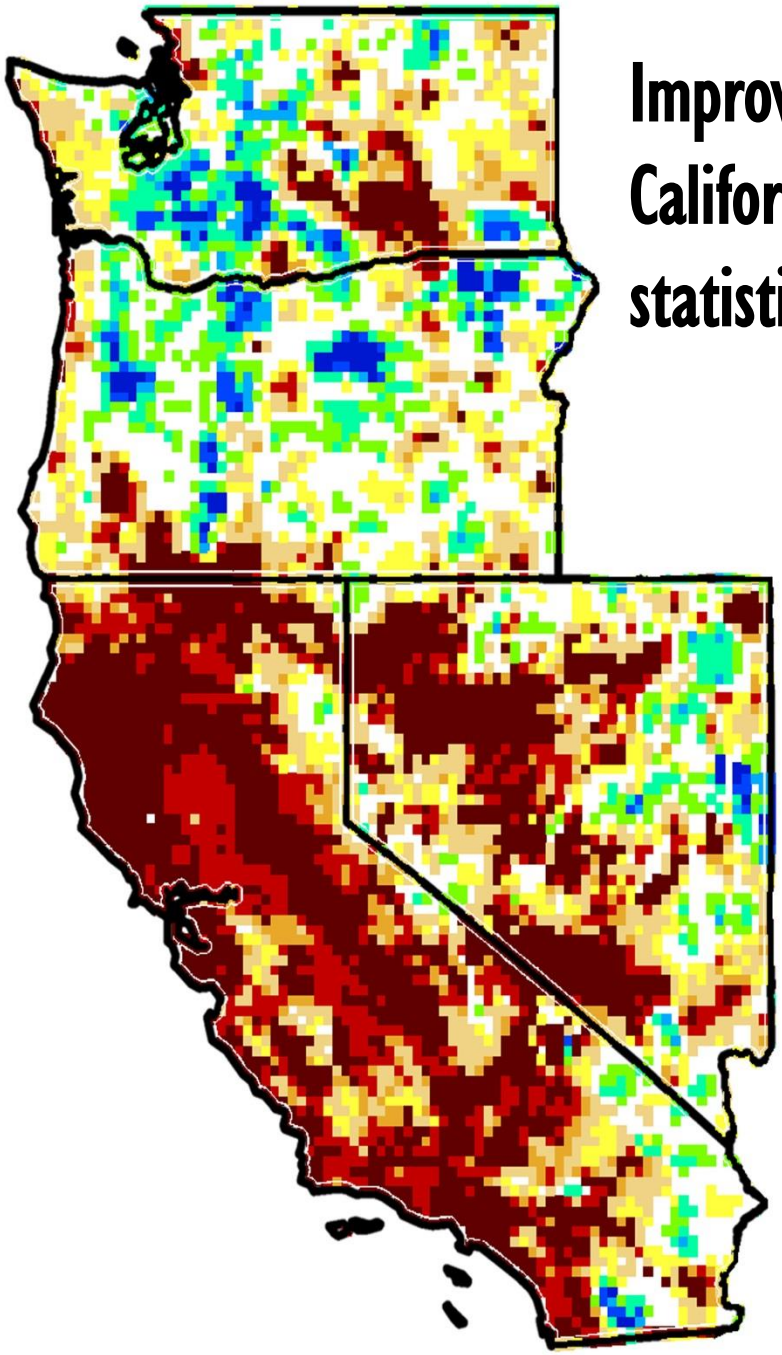
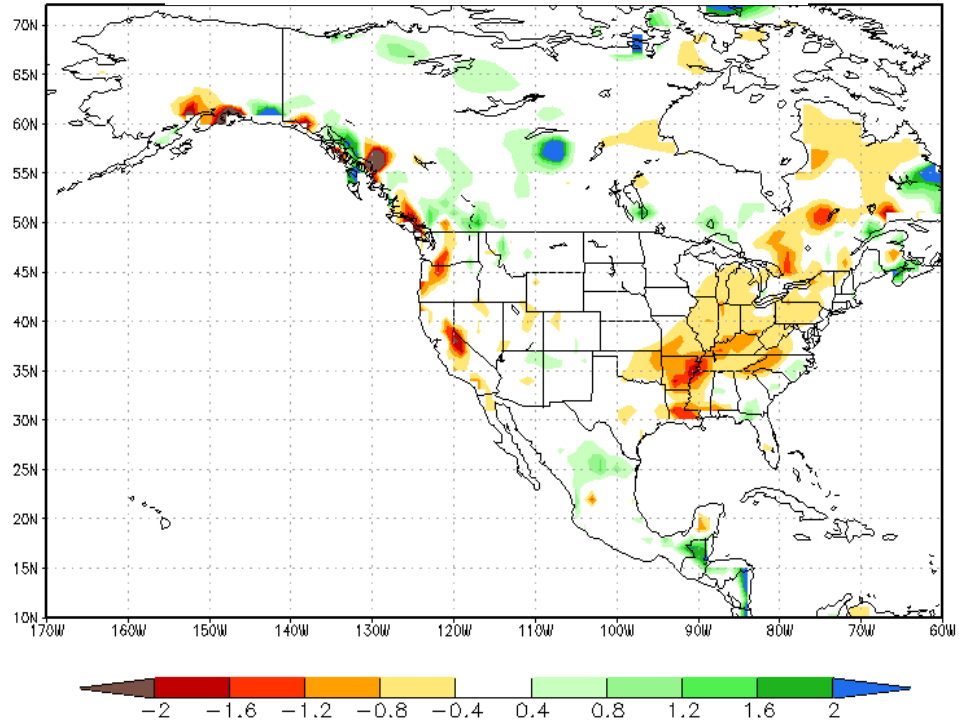


Improving seasonal precipitation forecasting in California through integration of dynamic and statistical models

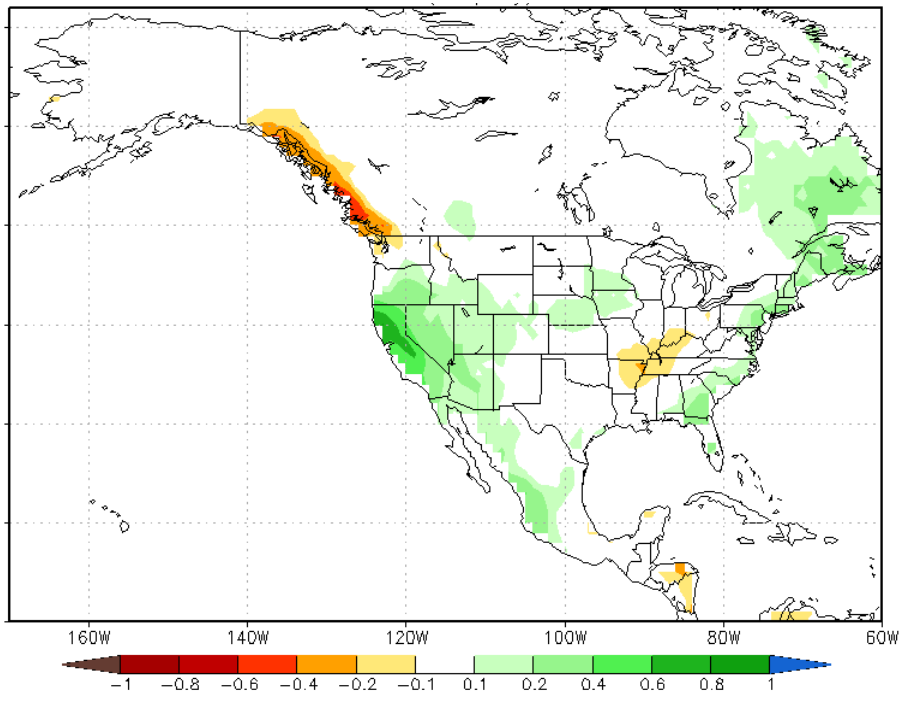
Amir AghaKouchak, Shahrbanou Madadgar, Linyin Cheng, Shrad Shukla, Andy Wood, Mark Svoboda

Motivation

Observed Precipitation Anomaly
DJF 2014



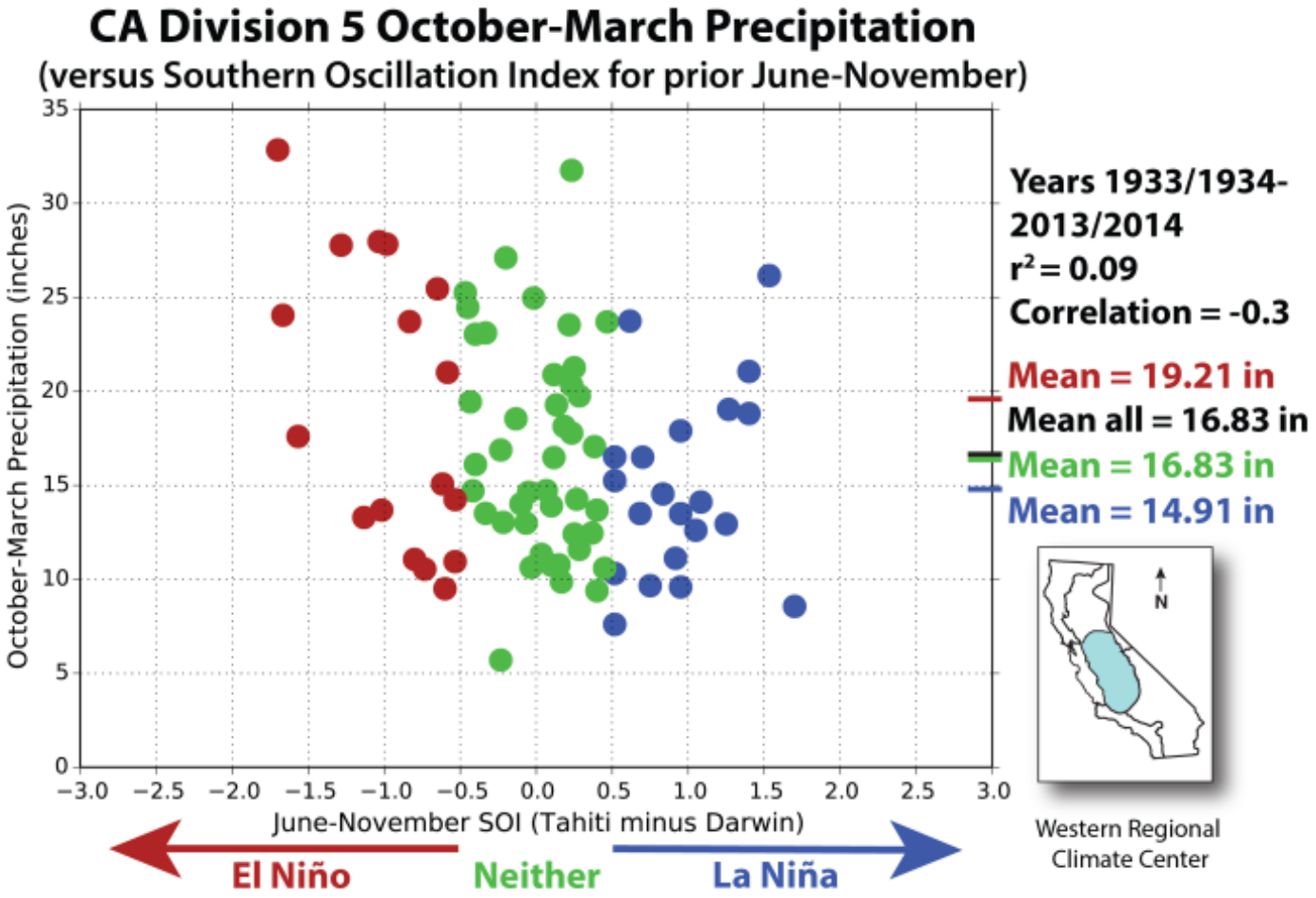
Predicted Precipitation Anomaly (mm/d)
DJF 2014 (Initialized: November)



North American Multi-Model Ensemble (NMME; Kirtman et al., 2014)

Low Predictability of Precipitation Forecasts in Dynamic Model Simulations

Motivation

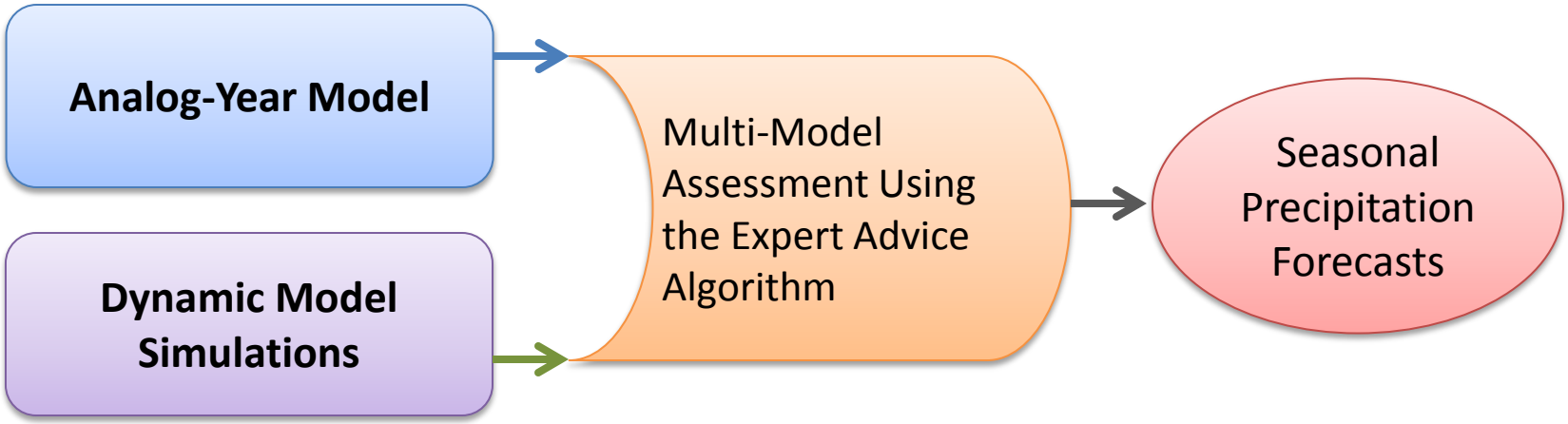


Kelley Redmond, DRI

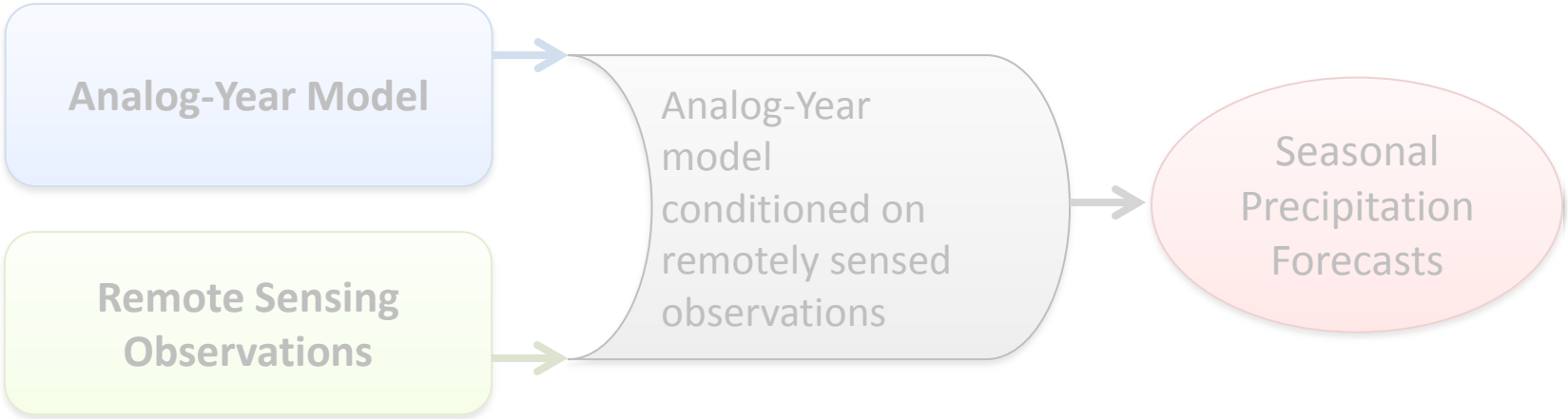
Analog-year based models also offer low predictability

Drought Prediction Frameworks

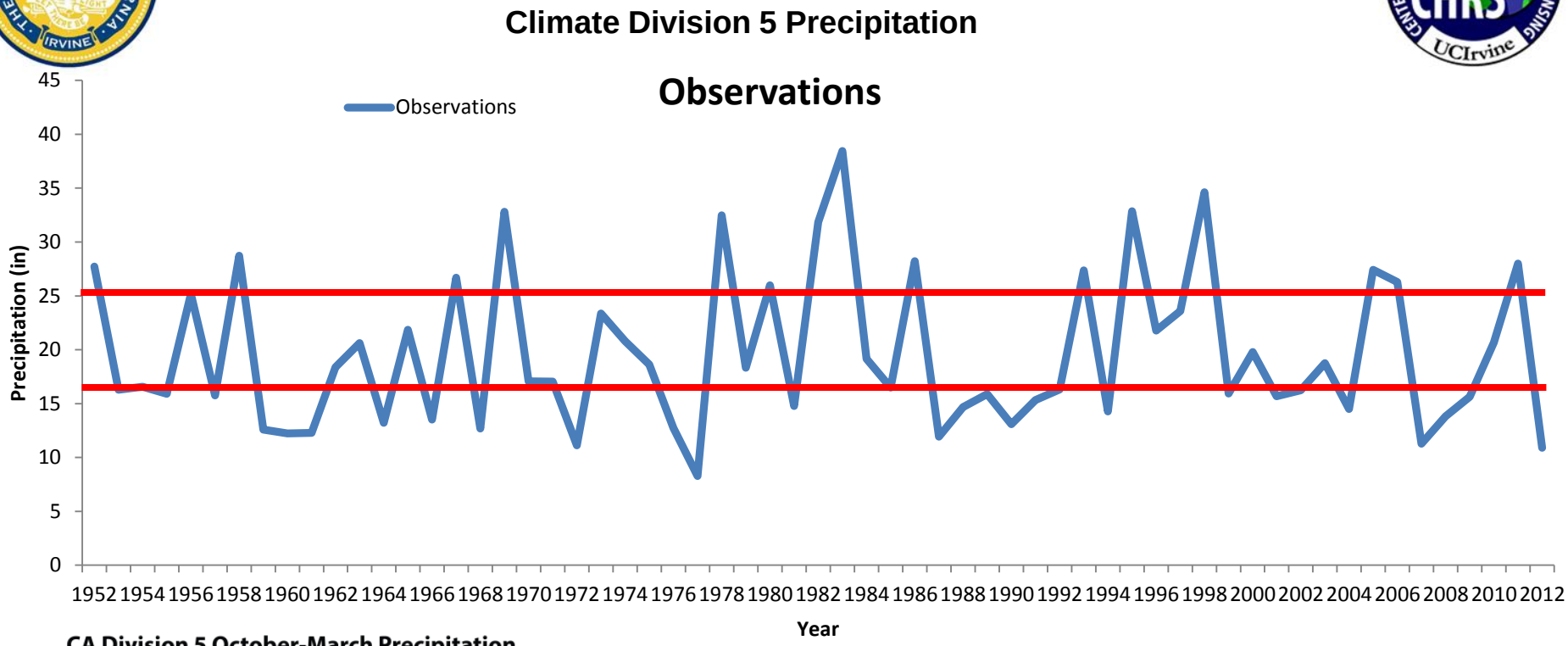
Analog-Year Model Combined Dynamic Model Simulations

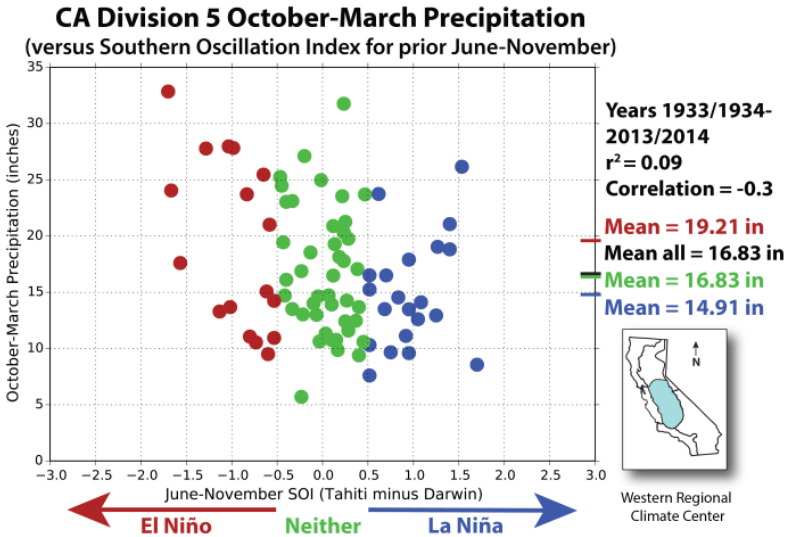


Analog-Year Model Combined with Remote Sensing Observations



Objective

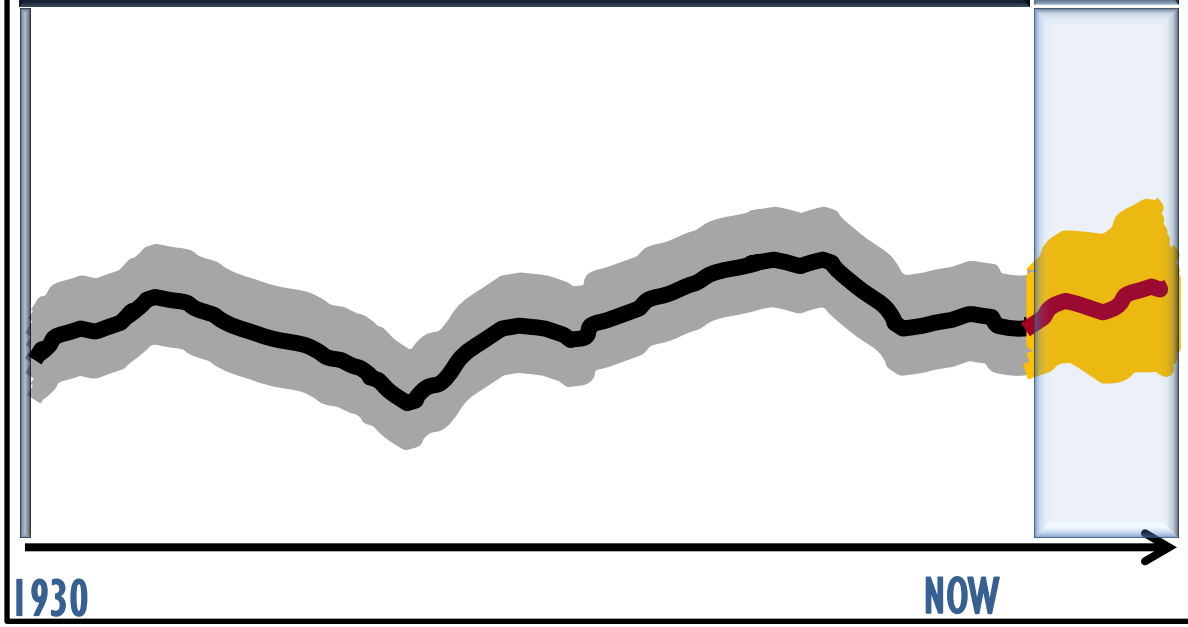




$$f(PDO, MEI, SOI, \dots) \sim \begin{cases} \Pr(P > AN) \\ \Pr(\mathrm{P} \sim \mathrm{NN}) \\ Pr(P < BN) \end{cases}$$

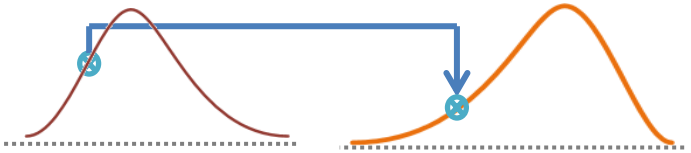
AN: Above Normal (> 66th Percentile)
NN: Near Normal
BN: Below Normal (< 33th Percentile)

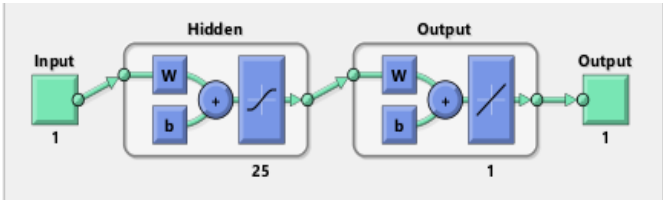
Long-Term Precipitation and Climate Oscillation Indicators



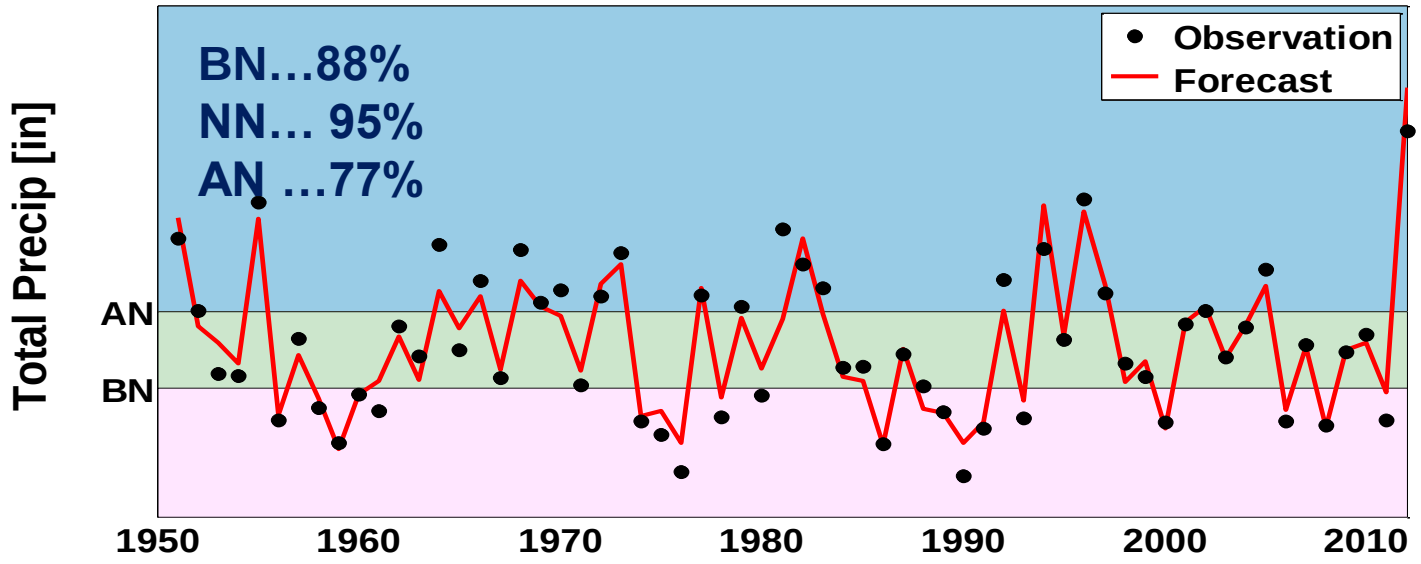
1- 6-Month Forecast

Past Climate $f(Precip_{Oct-Mar})$





Forecast Period= Oct-Jan



Precip. Climatology

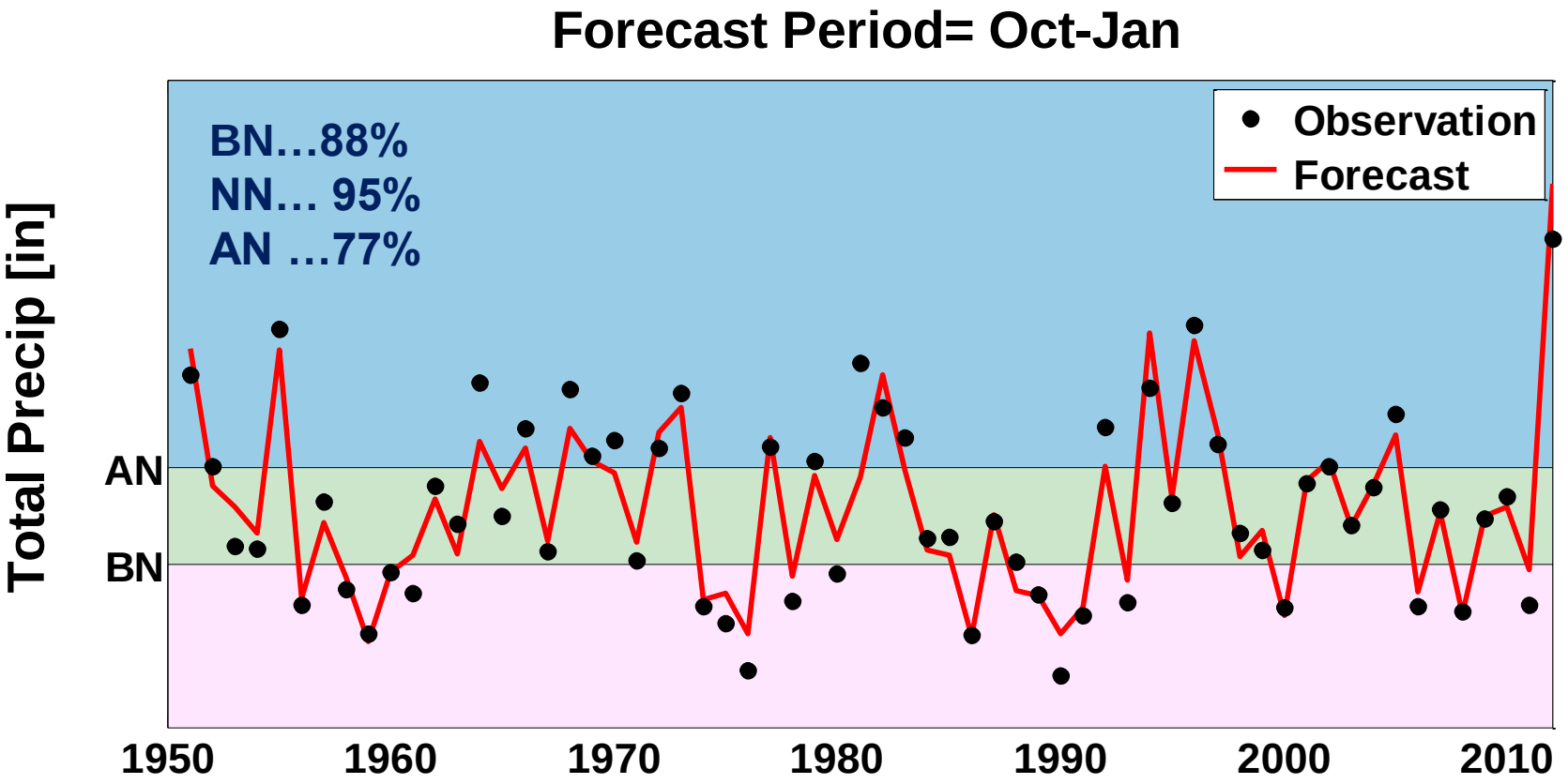
$SOI_{Apr-Sep}$,

$PDO_{Apr-Sep}$

$SPI_{Jun-Sep}$

Preliminary Results

- Climate Index: $SOI_{Apr\text{-}Sep}$, $PDO_{Apr\text{-}Sep}$
- $SPI_{Jun\text{-}Sep}$



Preliminary Results

- Climate Index: $SOI_{Apr-Sep}$, $PDO_{Apr-Sep}$
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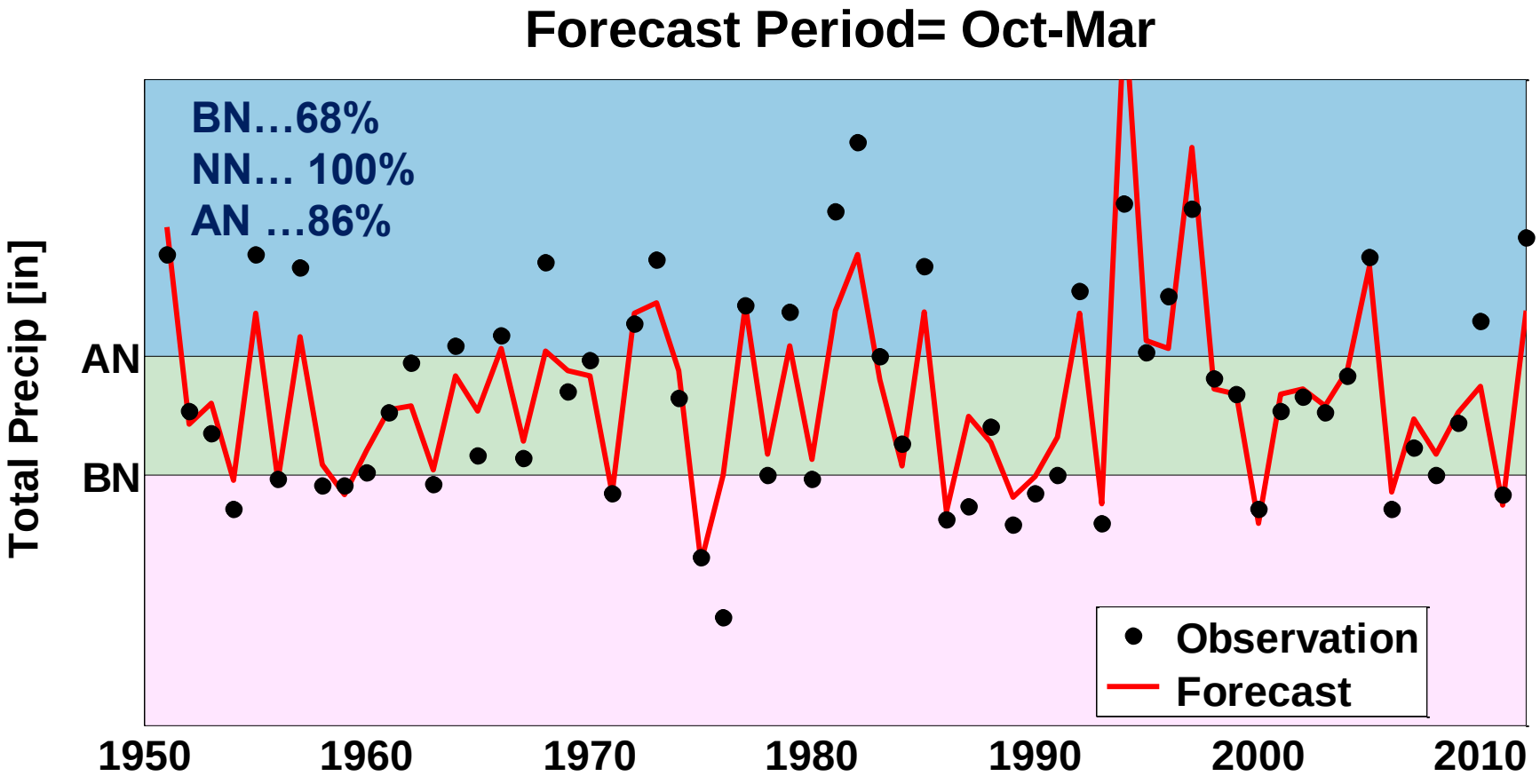
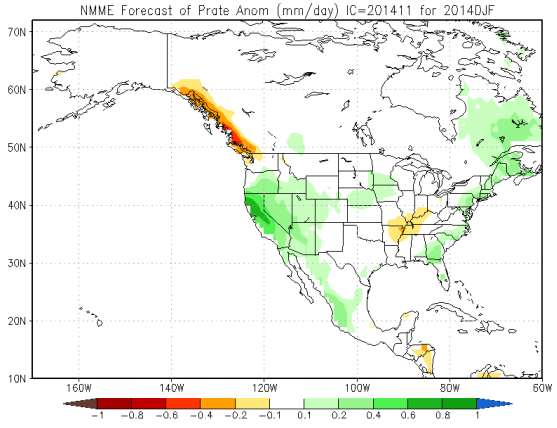
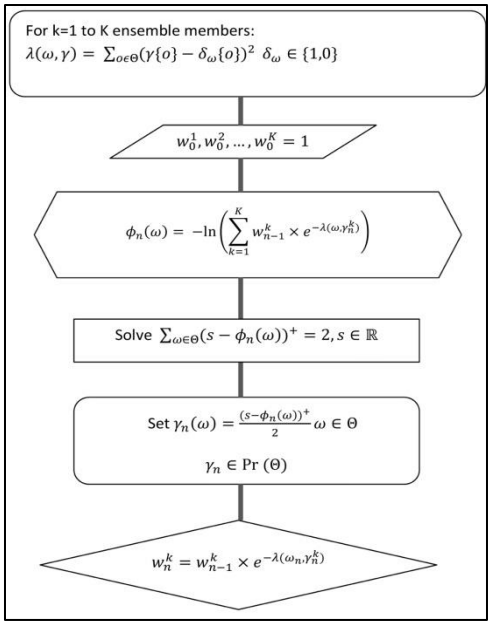
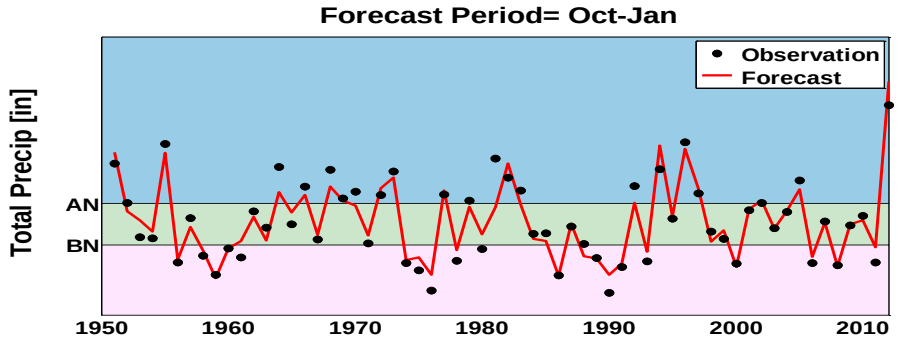


Drought Prediction Frameworks







Analog-Year Model

Dynamic Model Simulations

Multi-Model Assessment Using the Expert Advice Algorithm

Seasonal Precipitation Forecasts

Expert Advice (EA) Algorithm

For k=1 to K ensemble members:

$\lambda(\omega, \gamma) = \sum_{o \epsilon \Theta} (\gamma\{o\} - \delta_\omega\{o\})^2 \quad \delta_\omega \in \{1,0\}$

$w_0^1, w_0^2, \dots, w_0^K = 1$

$\phi_n(\omega) = -\ln\left(\sum_{k=1}^{K} w_{n-1}^k \times e^{-\lambda(\omega, \gamma_n^k)}\right)$

Solve $\sum_{\omega \in \Theta} (s - \phi_n(\omega))^+ = 2, s \in \mathbb{R}$

Set $\gamma_n(\omega) = \frac{(s - \phi_n(\omega))^+}{2} \omega \in \Theta$

$\gamma_n \in \Pr(\Theta)$

$w_n^k = w_{n-1}^k \times e^{-\lambda(\omega_n, \gamma_n^k)}$

EA concept leads to an ensemble response that is better than the best predictive model plus and an error term.

EA algorithm leads to dynamically changing ensemble member weights over time based on the performance of the model in similar conditions.

$E_0^1, E_0^2, \dots, E_0^K = 0$

Ensemble Member k: $\gamma_n^k \in \Psi$

Climate Response: $\gamma_n \in \Psi$

Observation: $\omega_n \in \Theta$

$E_n = E_{n-1} + \lambda(\omega_n, \gamma_n)$

$E_n^k = E_{n-1}^k + \lambda(\omega_n, \gamma_n^k)$

$E_n \leq \min_{k=1.....K} E_n^k + \ln K$

Cheng and AghaKouchak, 2015, J. Hydrology

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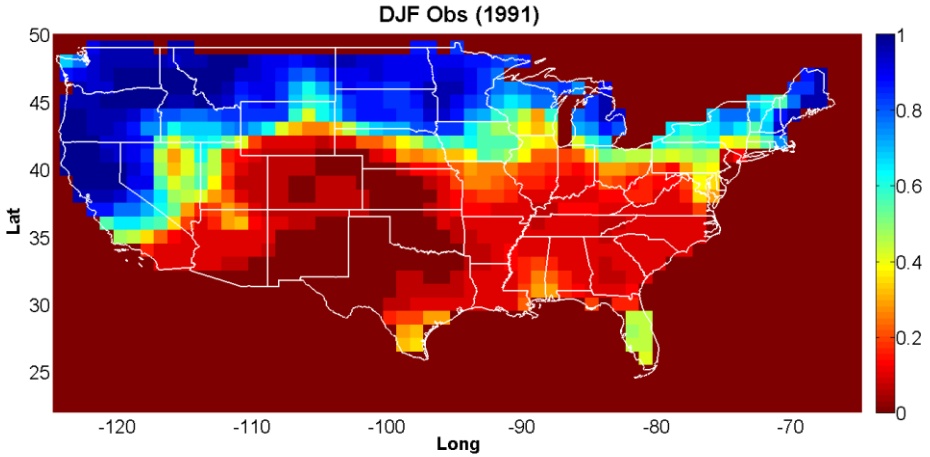
Ensemble Mean vs. Ensemble Response

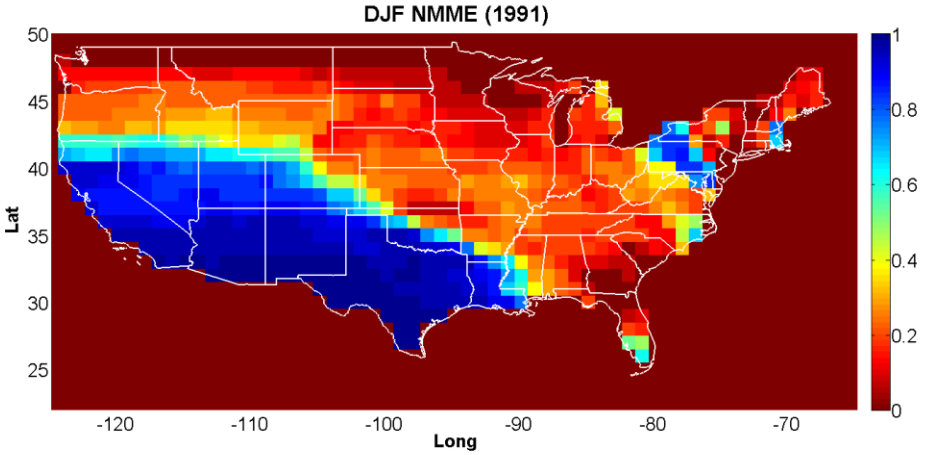
Cheng and AghaKouchak, 2015, J. Hydrology

Preliminary results, DJF - 1991

Obs-CMAP-URD

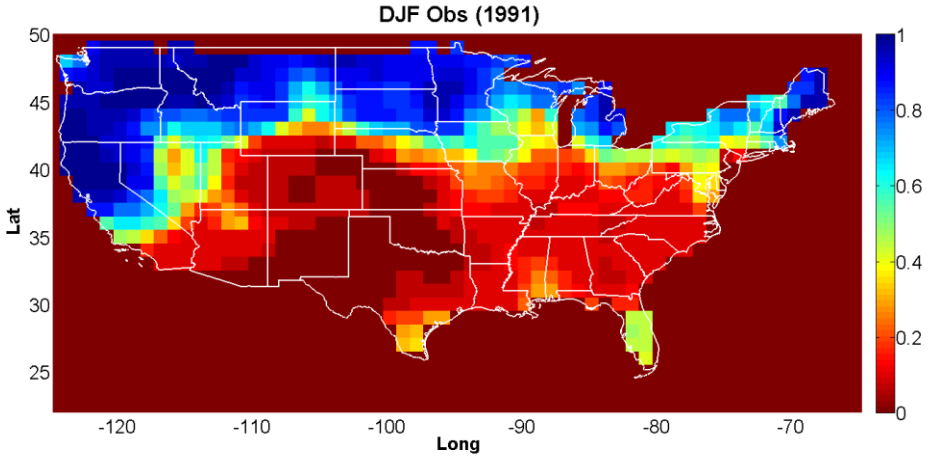


NMME (99 Ens members)

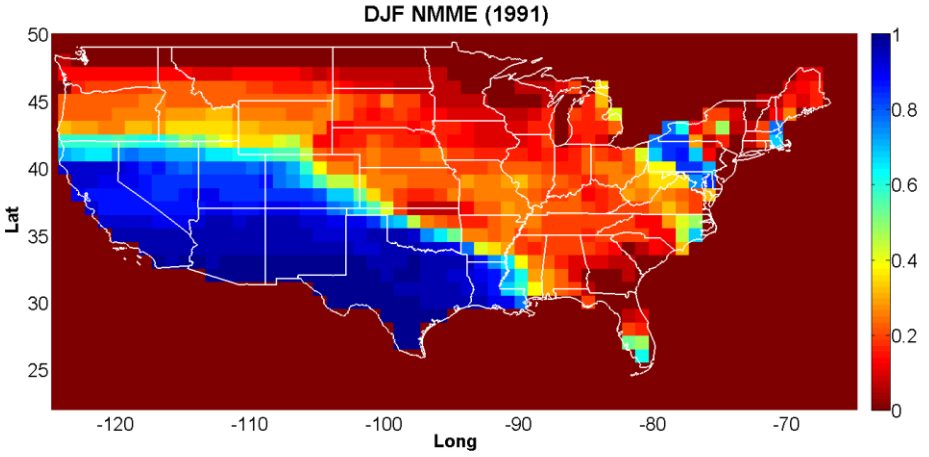


Preliminary results, DJF - 1991

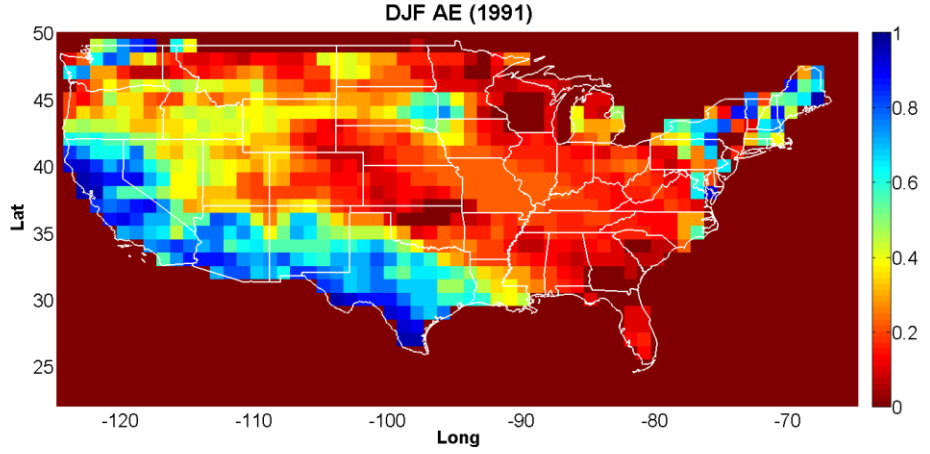
Obs-CMAP-URD



NMME (99 Ens members)

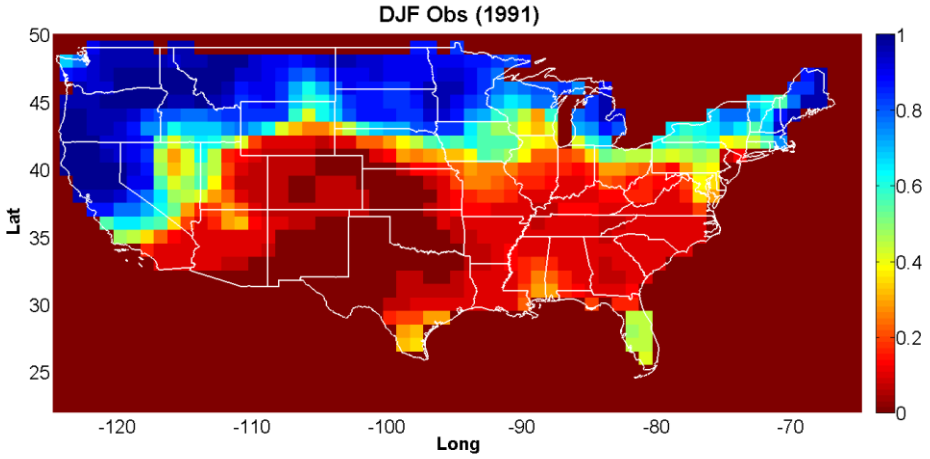


EA (99 Ens members)

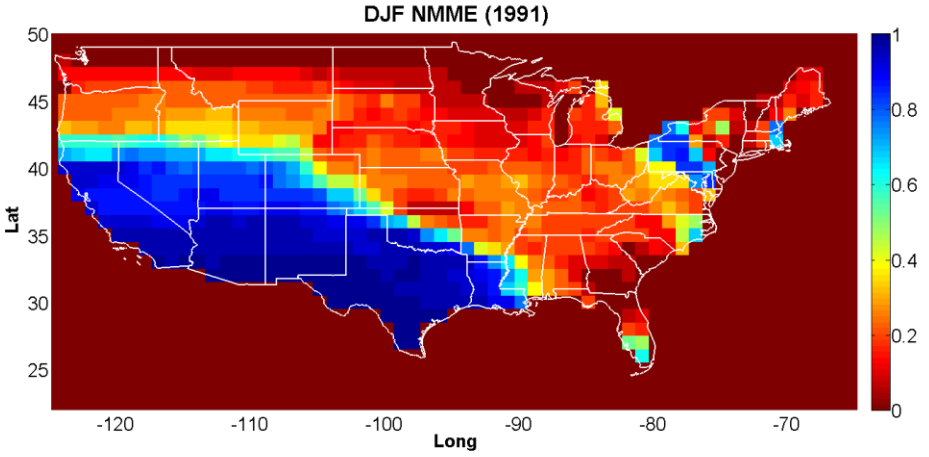


Preliminary results, DJF - 1991

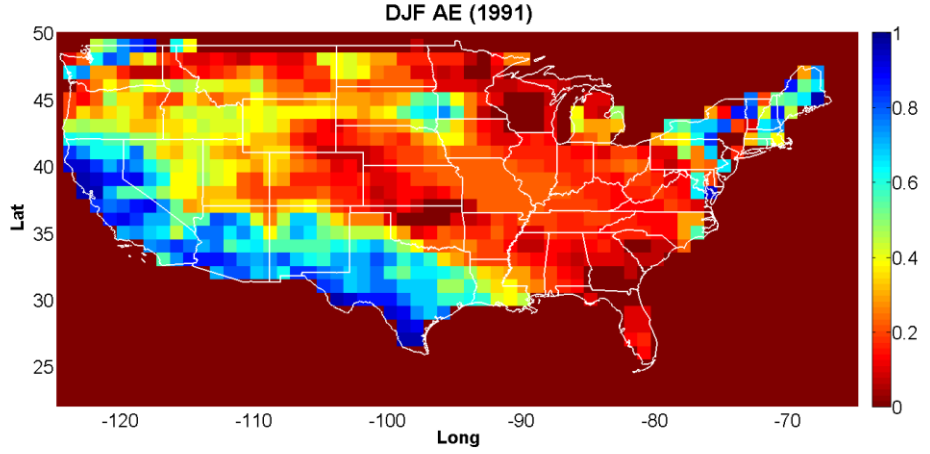
Obs-CMAP-URD



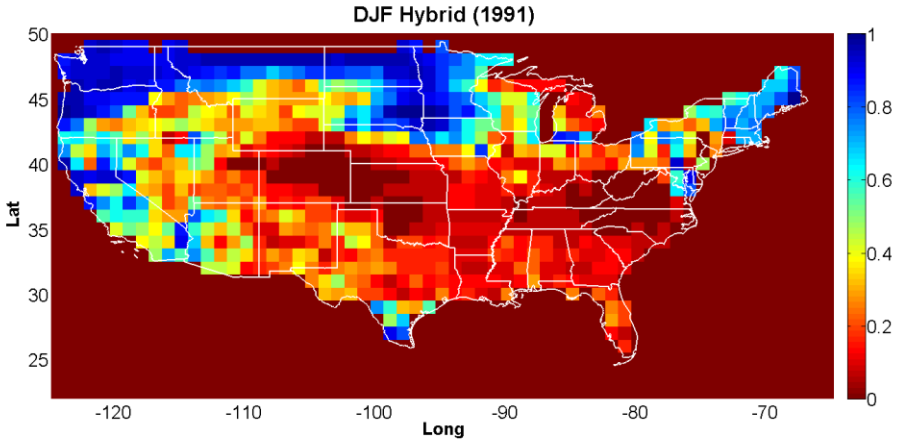
NMME (99 Ens members)



EA (99 Ens members)

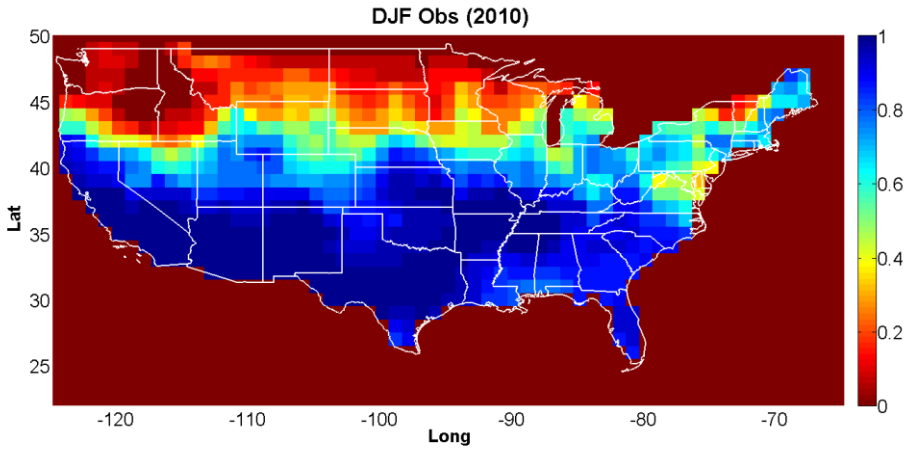


Hybrid Statistical-Dynamic Model

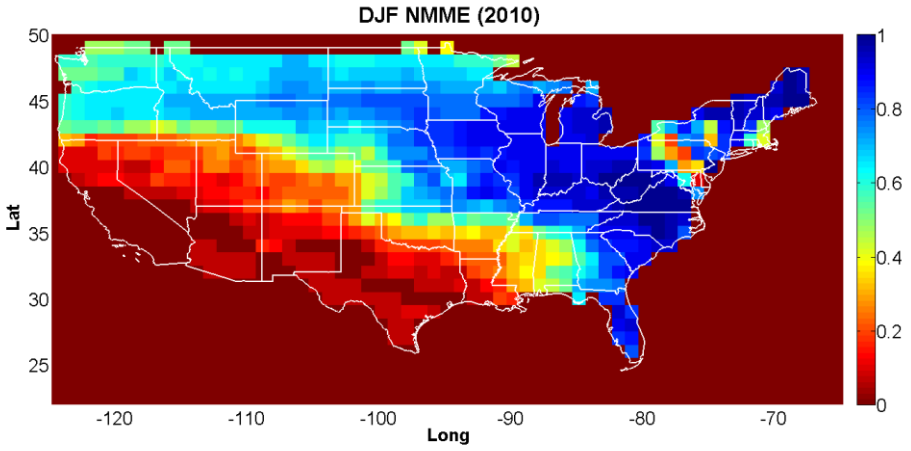


Preliminary results, DJF - 2010

Obs-CMAP-URD

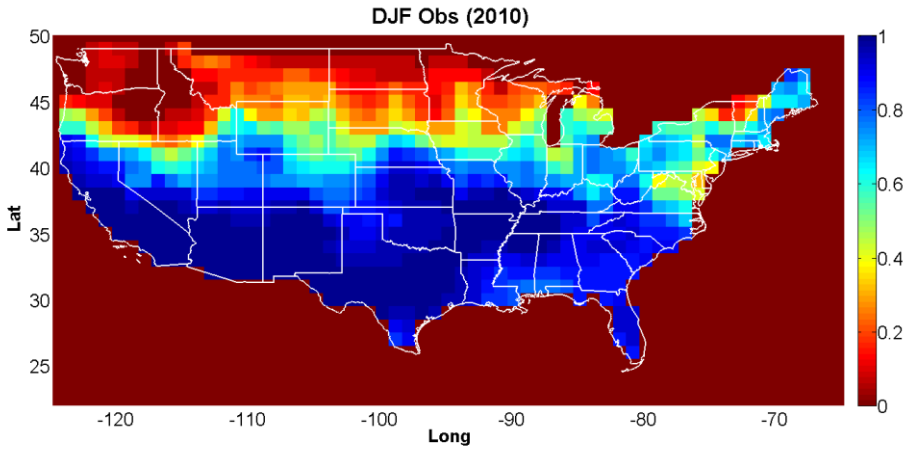


NMME (99 Ens members)

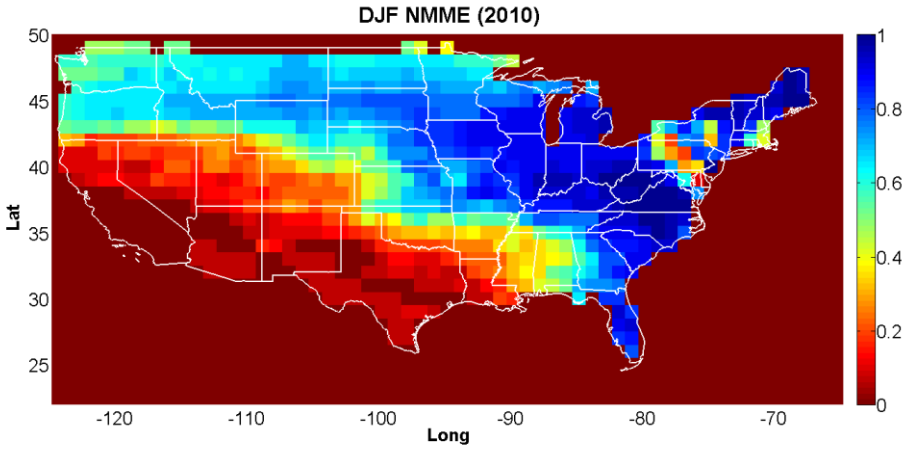


Preliminary results, DJF - 2010

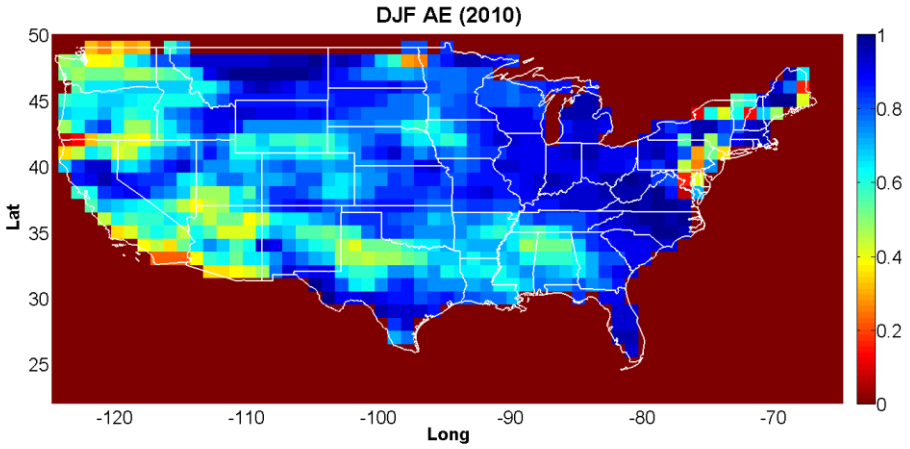
Obs-CMAP-URD



NMME (99 Ens members)

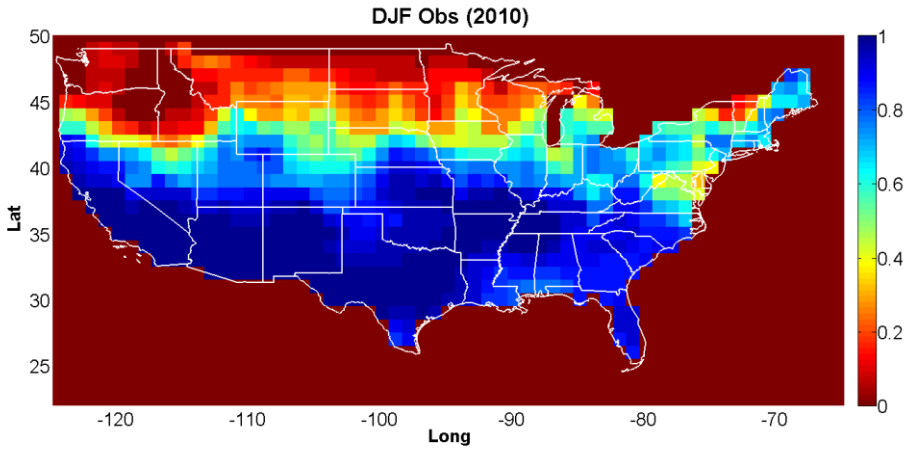


AE (99 Ens members)



Preliminary results, DJF - 2010

Obs-CMAP-URD



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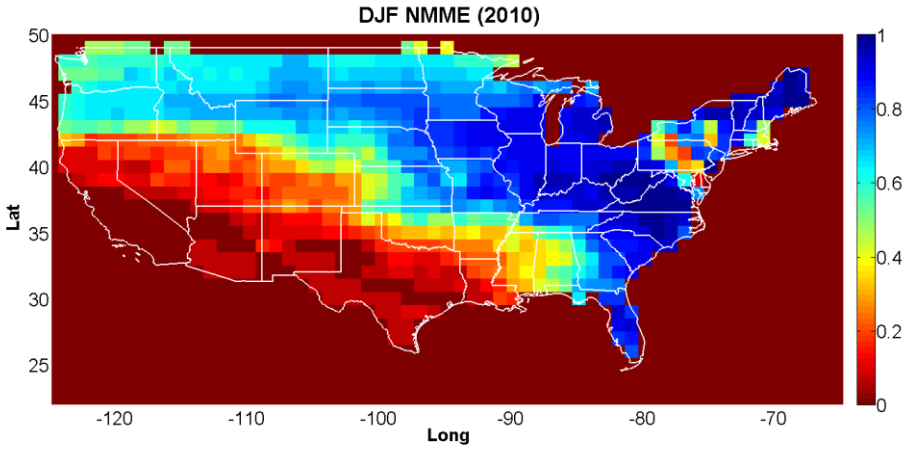

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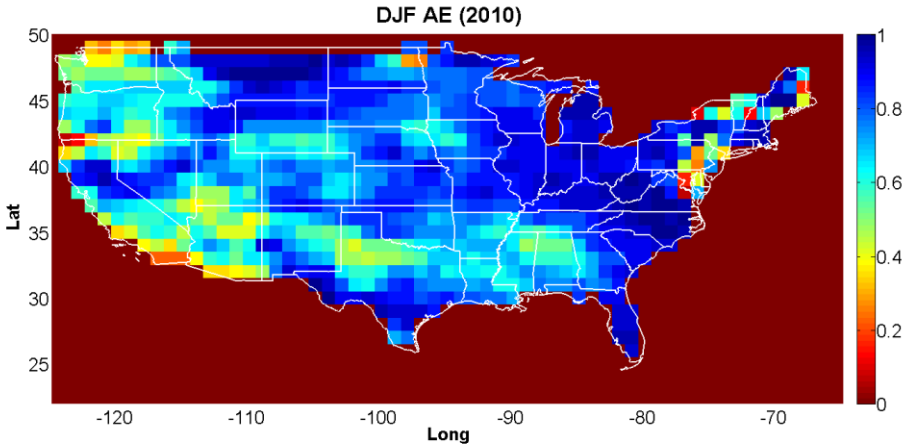
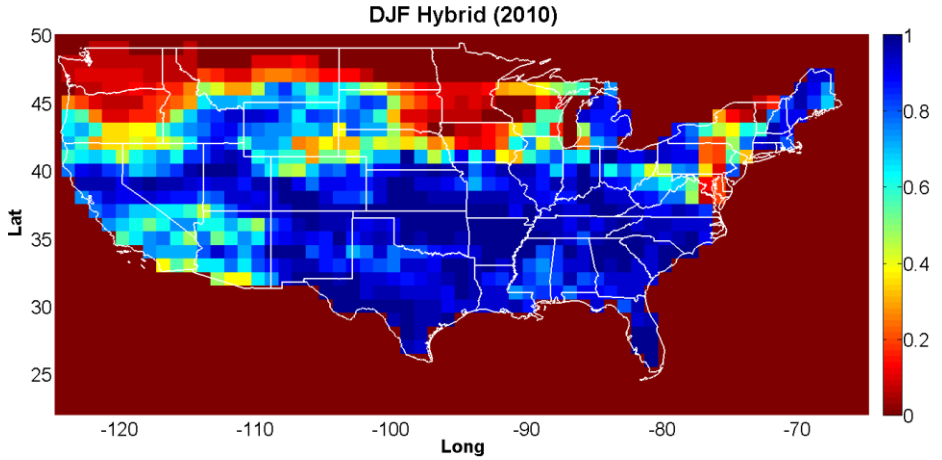


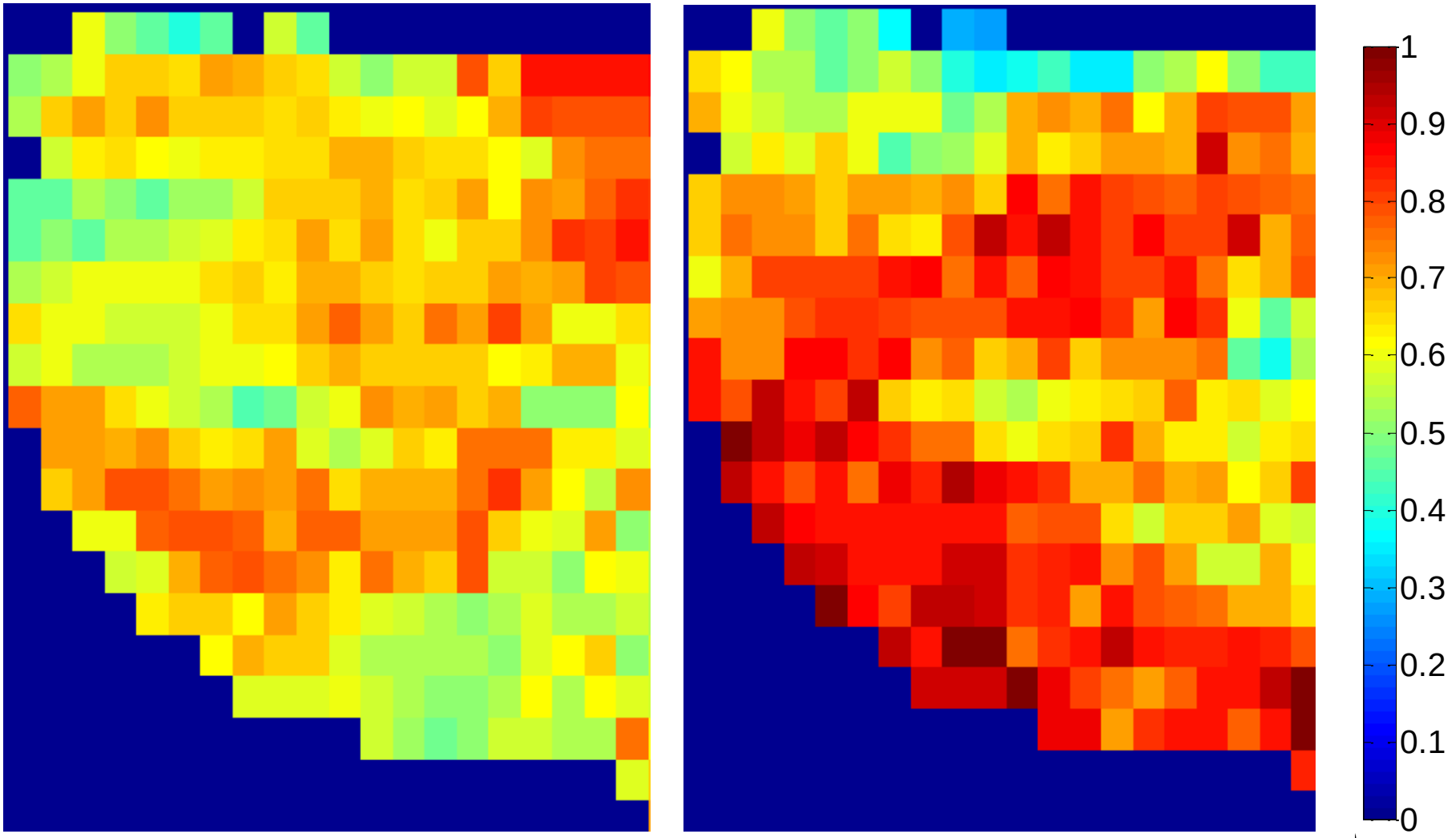
Hybrid Statistical-Dynamic Model



Drought Prediction

NMME (Ensemble Mean)

NMME + Analog-Year + AE (Hybrid Framework)



DJF Precipitation Forecasts - Fraction of the captured Negative Anomaly in all retrospective NMME forecasts 1981-2010

Questions?

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University of California, Irvine
Email: amir.a@uci.edu

We acknowledge support from:

NOAA and CA Dept. Water Resources,